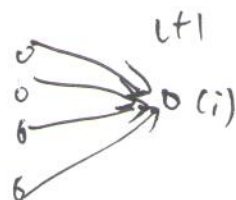


对于第 $l+1$ 层的第 i 个 neuron, 其输入

$$z_i^{l+1} = \sum_{j=1}^{S_l} \underbrace{W_{ij}}_{\text{weight}} \cdot a_j^l$$

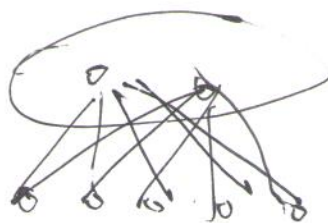


$$a_i^{l+1} = f(z_i^{l+1})$$

到了 N_L 层 (即 output layer)

以二分类为例:

一样的做法.



现对 N_L 层用 softmax. (这时一般用 cross entropy loss)

或者用不同 softmax, 直接 square-error.

fp:

① ^{BP} $J(w, b) = \left[\frac{1}{m} \sum_{i=1}^m J(w, b; x^{(i)}, y^{(i)}) \right] + \frac{\lambda}{2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} (w_{ji}^{(k)})^2$

m-training set. $\{x^{(1)}, y^{(1)}, \dots, x^{(m)}, y^{(m)}\}$

$$= \left[\frac{1}{m} \sum_{i=1}^m \left\| \frac{1}{2} \| h_{w,b}(x^{(i)}) - y^{(i)} \|^2 \right\| \right] + \frac{\lambda}{2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} (w_{ji}^{(k)})^2$$

②

$$w_{ji}^{(k)} = w_{ji}^{(k)} - \alpha \frac{\partial}{\partial w_{ji}^{(k)}} J(w, b)$$

$$b_i^{(k)} = b_i^{(k)} - \alpha \frac{\partial}{\partial b_i^{(k)}} J(w, b)$$

③

$$\frac{\partial J(w, b)}{\partial w_{ji}^{(k)}} = \frac{1}{m} \sum_{i=1}^m \frac{\partial}{\partial w_{ji}^{(k)}} J(w, b; x, y) + \lambda w_{ji}^{(k)}$$

$$\frac{\partial J(w, b)}{\partial b_i^{(k)}} = \left[\frac{1}{m} \sum_{i=1}^m \frac{\partial}{\partial b_i^{(k)}} J(w, b; x, y) \right]$$

④ 关键还是求 $\frac{\partial}{\partial w_{ji}^{(k)}} J(w, b; x, y)$ 和 $\frac{\partial}{\partial b_i^{(k)}} J(w, b; x, y)$

4.1 for the output layer, $\text{loss} = \frac{1}{2} \| y - h_{w,b}(x) \|^2$

$$\frac{\partial \frac{1}{2} \| y_i - h_{w,b}(x) \|^2}{\partial z_i^{(n)}}$$

$$h_{w,b}(x) = \sum a_i$$

$$= \frac{\partial \frac{1}{2} \| y_i - f(z_i^{(n)}) \|^2}{\partial z_i^{(n)}} = (y_i - f(z_i^{(n)})) \cdot (-f'(z_i^{(n)})) \quad \text{and } 0 = f'(z_i^{(n)})$$

即过程.

$$\bar{J}(w, b) = \frac{1}{m} \sum_{i=1}^m \frac{1}{2} \|h_{w,b}(x^{(i)}) - y^{(i)}\|^2$$

ground truth
Loss.

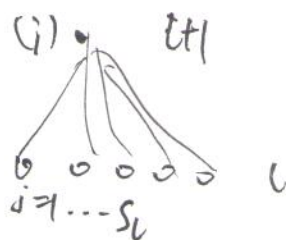
$$+ \frac{\lambda}{2} \sum_{l=1}^{L-1} \sum_{i=1}^{S_l} \sum_{j=1}^{S_{l+1}} (w_{ij}^{(l)})^2 \rightarrow \text{weight decay part.}$$

In example.

1.2. for $i = 1, 2, \dots, S_l$.

$$z_i^{(l)} = \sum_{j=1}^{S_{l-1}} w_{ij}^{(l-1)} a_j^{(l-1)}$$

$$a_i^{(l)} = f(z_i^{(l)})$$



现在定义一个概念. sensitivity. $\delta_i^{(l)}$ 表示的是第 l 层的第 i 个 neuron

its activation. 对 output 的 loss 的 responsibility. 如果 $\delta_i^{(l)}$ responsibility 很大, 说明 $a_i^{(l)}$ 对 loss 很敏感, vice versa, 所以 $\delta_i^{(l)}$ 叫 Sensitivity

neuron activation 对 general loss 的 sensitivity.

$$\delta_i^{(l)} = \sum_{j=1}^{S_{l+1}} (w_{ji}^{(l)} \delta_j^{(l+1)}) f'(z_i^{(l)})$$



这样便定义了 error 的 l 's layer to $l+1$'s layer.

$$4.3. \frac{\partial \bar{J}(w, b; x, y)}{\partial w_{ij}^{(l)}} = a_j^{(l)} \cdot \delta_i^{(l+1)}$$

$$\frac{\partial \bar{J}}{\partial w} = \left(\frac{\partial \bar{J}}{\partial a} \right) \frac{\partial a}{\partial w} = \delta_i^{(l+1)} \cdot a_j^{(l)}$$

$$\frac{\partial \bar{J}}{\partial b} = \frac{\partial \bar{J}}{\partial a} \cdot \left(\frac{\partial a}{\partial b} \right)$$